

## Countermine Lidar UAV-based System (CLUBS)-Year 2

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### LONG-TERM GOALS

The long-term goal of this work is to examine the utility of commercial bathymetric lidar technology solely, and in combination with commercial passive imaging spectrometers, for measuring environmental information for military applications in the littoral zone. These findings will indicate how commercial systems might evolve to achieve improved performance for rapid environmental assessment and for deployment in unmanned aerial vehicles.

### OBJECTIVES

1. Develop capability to produce lidar-only classification of the seafloor.
2. Develop capability to estimate underwater horizontal visibility from bathymetric lidar data.
3. Identify the best strategy for integrating a few spectral channels of passive data with lidar data for seafloor and water column characterization.
4. Assemble combined active and passive datasets over a range of environments and environmental conditions.

### APPROACH

We developed physics-based methods for generating normalized waveforms and seafloor reflectance images from a calibrated bathymetric lidar. Then, we analyzed these images and waveforms, along with geometric data computed from the depth measurements, to produce lidar-only classifications of the seafloor. Subsequently, we combined lidar-derived depth, seafloor reflectance, and water column attenuation (estimated at 532 nm) to conduct constrained inversion of simultaneously-acquired passive spectral images. We then explored methods to combine the active and passive seafloor images to improve seafloor classification. We conducted field data campaigns coincident with airborne data collections to provide high-quality in situ measurements, and used these data to support algorithm development. We developed software in the IDL programming language, instantiated within the ENVI image processing environment, to sequentially process all airborne datasets and produce desired seafloor classifications and accuracy assessments.

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## WORK COMPLETED

Using in situ measurements of seafloor reflectance (measured with Divespec instrument), and water column measurements (measured by the University of Southern Mississippi under subcontract to us) we refined algorithms and software to produce lidar-derived seafloor reflectance images using the power equation, and conducted accuracy assessments of these images. We then developed new algorithms for estimation of reflectance from energy equations, and demonstrated the equivalence of the power and energy approaches for this purpose.

We implemented new approaches to extract information from lidar-derived seafloor reflectance images by application of wavelet based decompositions of the images, and we implemented procedures to create an information feature space based on the shape of the bottom return in individual waveforms. We also refined our procedures for generation of rugosity metrics from the digital depth models and combined these features into a lidar feature space.

We refined our data processing flow and algorithms for the constrained inversion of passive spectral data to produce estimates of passive seafloor reflectance, and added these spectral images to the lidar information features to generate an extended feature space. These refinements in the inversion procedure included the addition of water column volume reflectance and attenuation at 532nm.

We implemented a procedure, based on receiver operating curve (ROC) analysis, to analyze the information content in the extended feature space and support selection of most valuable information features.

We integrated all developed software modules into a single package called the Optech Rapid Environmental Assessment (REA) Processor, and created efficiencies to accelerate the performance of the code.

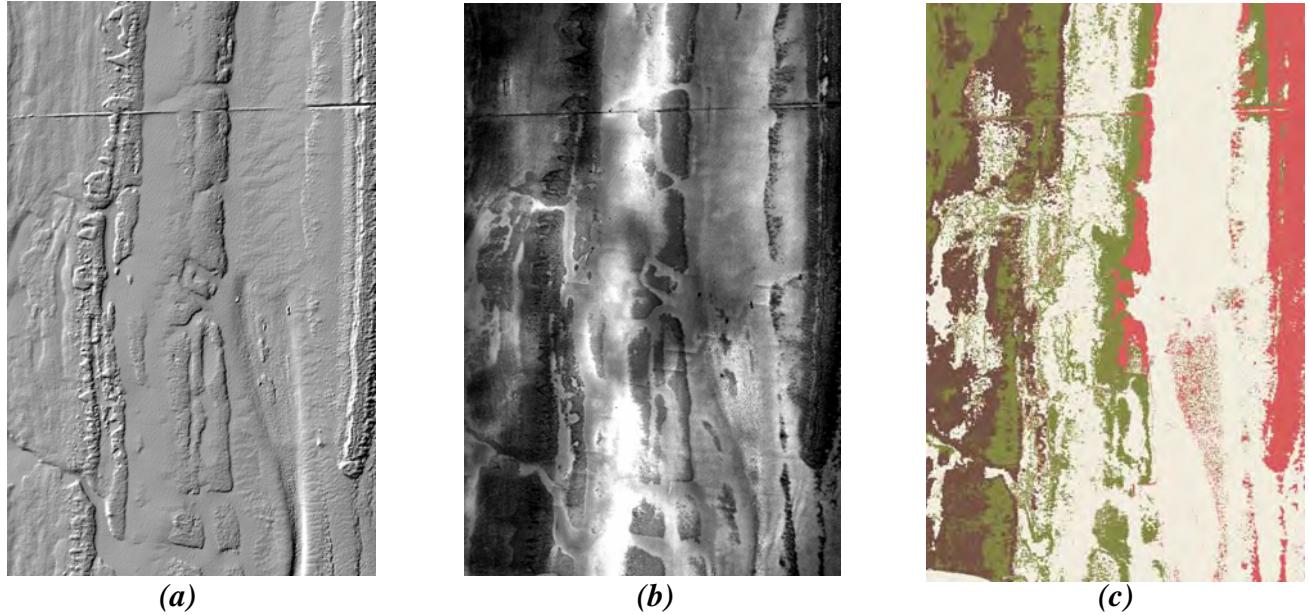
We conducted a new data acquisition campaign in the Great Lakes which contained airborne and in situ data. This data collection was organized in response to critique of year-1 results by government personnel who suggested the techniques should be tried in a wider range of environmental conditions.

We began organizing the data and software for final delivery to ONR and generation of the project reports.

## RESULTS

To date, our results indicate lidar data alone can be used to map the seafloor into classes of hardbottom, reef, sand, coral, and mud, in depths between 8m and 30m. In this depth range, passive images only slightly improve the accuracy, suggesting these classes are well-described by a combination of differences in green reflectance and variations in seafloor topography. In shallower waters, the accuracy of lidar-only classifications often decreases as the accuracy of lidar-derived reflectance decreases. This decrease is caused by errors in the estimation of lidar system attenuation in shallow water, and those errors arise from difficulties in picking interest points on the volume backscatter part of individual waveforms.

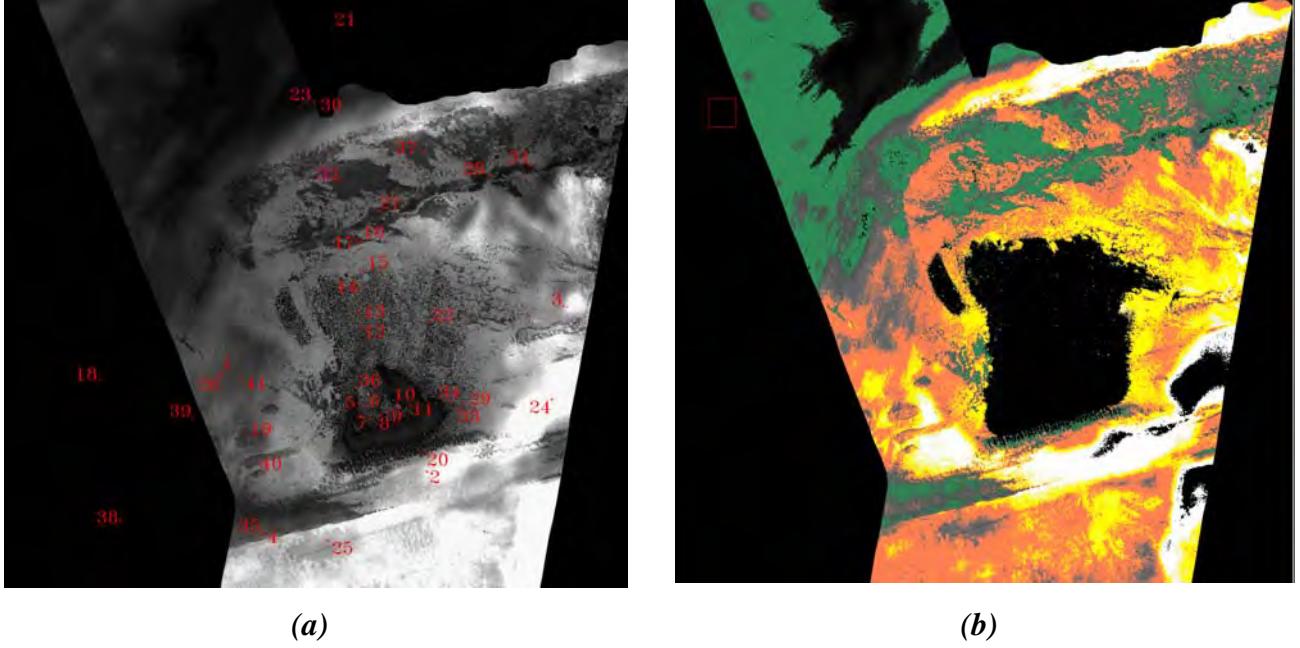
In Figure 1, we demonstrate successful lidar-only classification in waters greater than 8m. Here, we show the seafloor topography, reflectance, and classification images for the seafloor near Fort Lauderdale, generated with the Optech REA Processor and data from the SHOALS system. The classification was accomplished using the REA ROC analysis tool to select only SHOALS features having a ROC value greater than 0.7. Comparison to groundtruth (produced independently by researchers at the National Coral Reef Institute) indicates this classification has an overall accuracy of 76%, and a Kappa coefficient of 0.67. The classification is only moderately improved through the addition of spectral images. For example, extending the classification feature space to include spectral seafloor images produced from CASI data improved the accuracy to only 77%.



**Figure 1. bathymetric lidar images and classification produced with the REA processor. (a) seafloor topography, (b) seafloor reflectance (532nm), (c) seafloor classification produced using nearest neighbor algorithm on lidar-derived information features (white-sand; brown-hard bottom; green-inner reef; coral-outer reef). (These images are about 2.3km x 3.3km and used 17 overlapping flightlines of simultaneous SHOALS and CASI data)**

Green reflectance alone (or even pseudoreflectance computed using a constant value of attenuation) can often be used to produce seafloor classifications in shallow waters using simple thresholding techniques. For example, we show in Figure 2, pseudoreflectance and classification maps of Looe Key produced using the pseudoreflectance value from the lidar at 532nm to select the appropriate seafloor spectral signature from a spectral library. Inspection of the classification map reveals we were unable to classify the seafloor in very shallow waters (less than 2m). For this reason, the area around Looe Key itself is shown as black. The misclassification arises from 2 errors in seafloor reflectance data. First, any errors in the measured depth from the SHOALS depth extractor create subsequent errors in reflectance. Second, any error in the estimation of water column attenuation in the REA processor creates errors in reflectance. Both type of errors are manifested in this dataset and are related to the

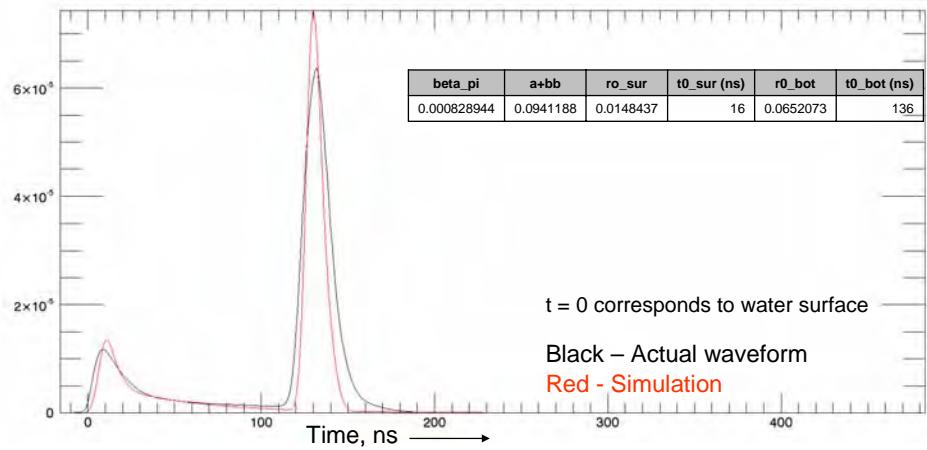
shallow water performance of the SHOALS system. Consequently, the Looe Key data have been valuable with respect to refining the accuracy of the seafloor reflectance images in very shallow waters.



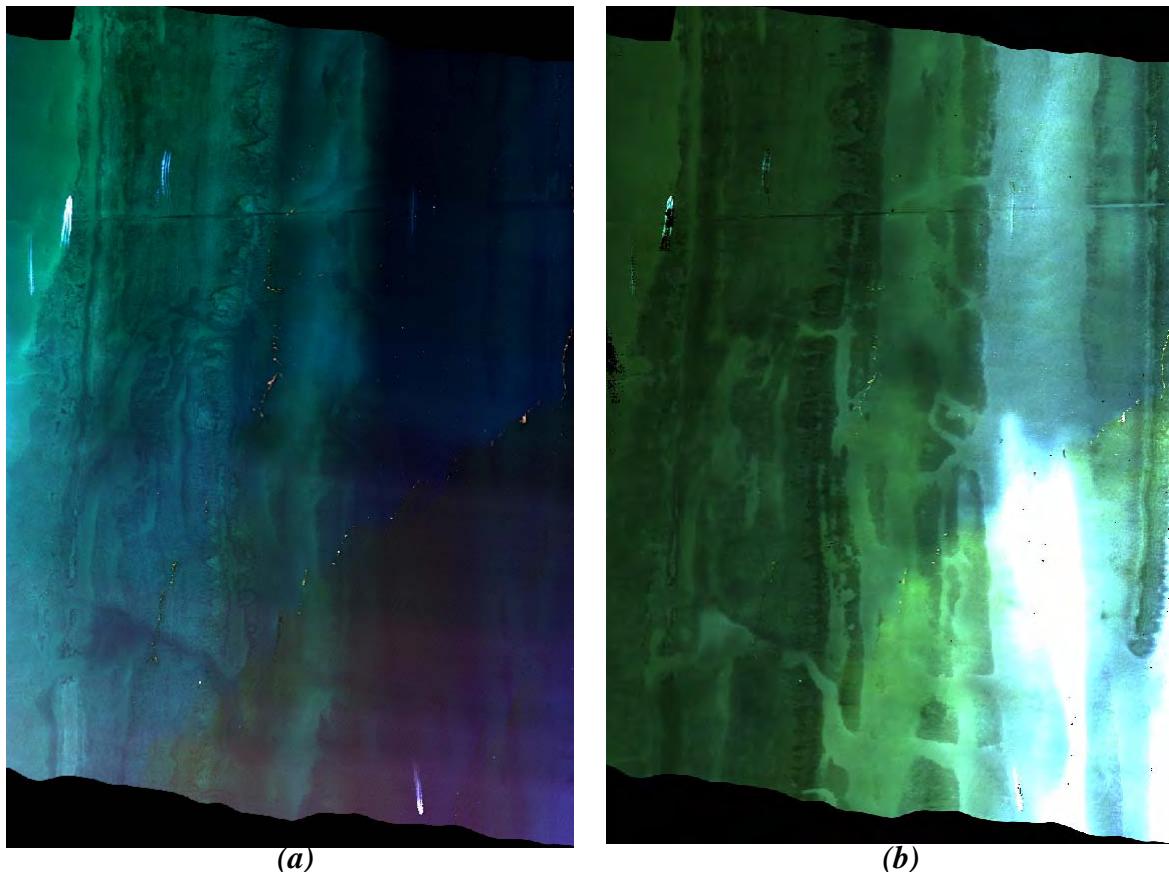
**Figure 2. Seafloor reflectance (a) and classification image (b) generated by thresholding the lidar-derived seafloor reflectance image using diver-measured values of reflectance. Green areas correspond to vegetated bottoms (seagrass or reef organisms). Coral color depicts sand, and yellow and white colors represent areas above the standard deviation of the diver-measured reflectance of sand. (above 0.44).**

Realizing the importance of this shallow water problem, we implemented a new approach to processing bathymetric lidar waveforms based on the decomposition of each waveform into components. We believe this strategy holds promise for improving estimates of all parameters (including depth). For example, we show in Figure 3, the decomposition of a single waveform into components to yield estimates of  $B_\pi$ ,  $a+b_b$ , surface reflectance, surface detect timebin, seafloor reflectance, and seafloor detect timebin. The timebin estimates can be used to yield new computations of depth. To date, we have tested this procedure on only a few waveforms and have yet to develop operational code to efficiently handle millions of waveforms of a typical lidar dataset.

We have found the fusion-based constrained inversion technique, ambiguity search, does not produce high-quality seafloor spectral reflectance images when the water column characteristics vary widely over a small geographic area [1]. To improve the method, we developed techniques to estimate water column volume backscatter from the lidar data, and implemented changes to the lidar seafloor reflectance algorithms. Based on these improvements, we changed the constraints so that seafloor reflectance from lidar was used to select an endmember for spectral reflectance, and this endmember



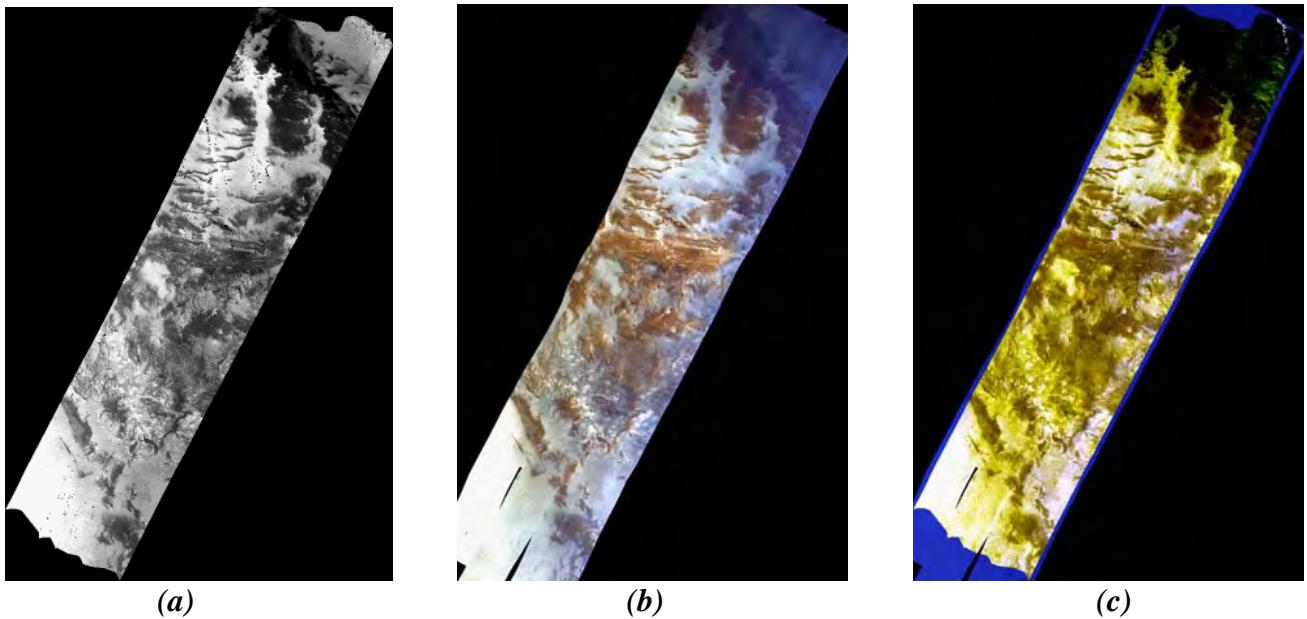
**Figure 3. Waveform decomposition approach to parameter estimation in bathymetric lidar**



**Figure 4. CASI water leaving reflectance (a) and seafloor reflectance image (b) of Fort Lauderdale produced with the REA Processor (R:645nm; G:532nm; B:455nm )(same area as Figure 1)**

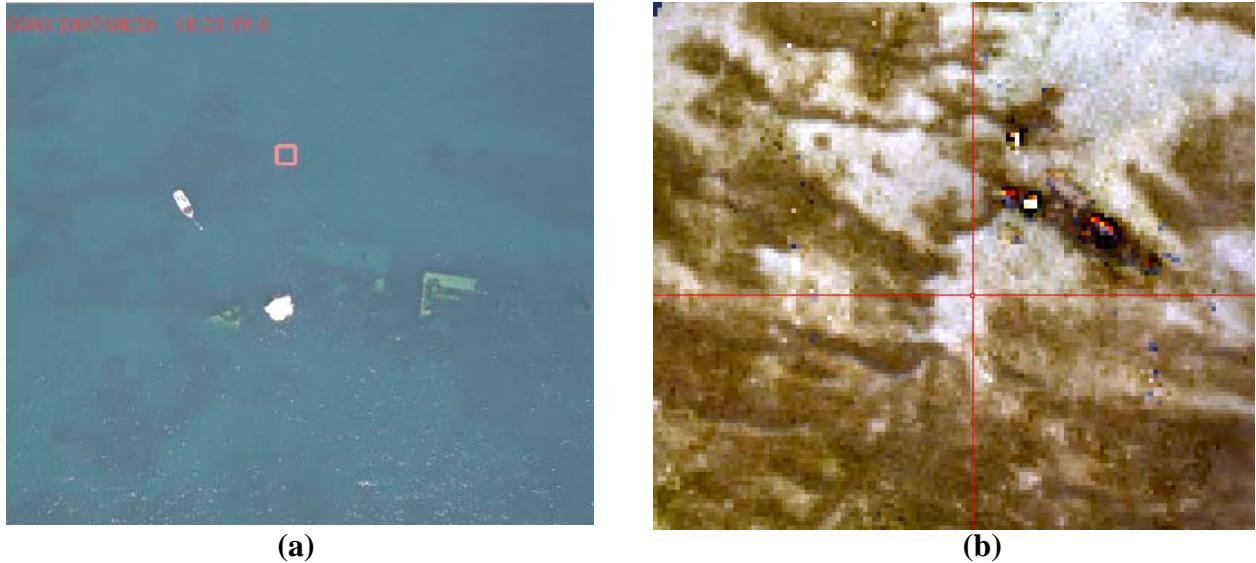
was subsequently used as a weak constraint in the ambiguity search inversion (we continued to use depth from the lidar as a fixed constraint). In Figure 4, we show the surface reflectance and seafloor reflectance images produced using these improvements to the REA processor. This area of the Fort Lauderdale dataset has proved challenging because of the sharp attenuation boundary in the water column caused by the presence of sand spilled from a dredge (visible in the lower right corner of the image).

During the project brief at the end-of-year-1, government personnel suggested collection of a dataset over darker seafloor types (non-carbonate environment). Based on this input, we conducted a data collection campaign in Lake Huron at Thunder Bay National Marine Sanctuary using the CHARTS system operated by JALBTCX as the data collection platform. The seafloor in this area is composed of sand, bedrock, cobble, and algae and there are numerous interesting ship wrecks. In Figure 5 we show SHOALS seafloor reflectance, CASI surface reflectance, and CASI seafloor reflectance images generated with the REA processor, for a few flightlines of data. Seafloor classifications have not yet been completed but we are anticipating successful results based on the high quality of the active and passive seafloor images.



**Figure 5. SHOALS seafloor reflectance (a), CASI water leaving reflectance (b), and CASI seafloor reflectance (c), in Thunder Bay National Marine Sanctuary (R:570nm; G:531nm; B:455nm). (These data collected in July of 2007 using CHARTS system).**

To further demonstrate the high quality of these data, we show in Figure 6 a digital photograph made with the CHARTS camera of the *in situ* vessel over a shipwreck. Part (b) of the figure shows the CASI seafloor reflectance image generated using the REA processor. Here, the light color is sand and the darker color is algae-covered bedrock and cobble.



**Figure 6. Digital photograph (a) showing in situ boat moored near wreck in Thunder Bay. CASI seafloor reflectance image (b) produced with REA processor of same area. Seafloor here is sand and algae-covered bedrock and cobbles.**

## IMPACT/APPLICATIONS

Our results indicate that bathymetric lidar alone can be used to classify the shallow water seafloor with accuracies approaching 80%. Due to the long system response function of SHOALS, classification accuracies tend to decrease in waters shallower than 8m, and become very difficult in waters as shallow as 2m. These problems may be improved by the application of the waveform decomposition approach, but to date, that technique has been demonstrated only with a few waveforms. These findings provide valuable insight for design and construction of the next generation of airborne coastal mapping and imaging systems.

All algorithms and software have been integrated into a single software package called the Rapid Environmental Assessment (REA) Processor. REA can be used to produce co-registered raster images from the bathymetric lidar and spectrometer, and can be used to produce seafloor reflectance images from the passive at-sensor radiance data. Other tools within REA support the extraction of information features from an extended active/pассив dataset, and analysis of these features to choose the most valuable features for classification purposes. Finally, the software provides for conducting the classification and accuracy assessment. Our intent is to ultimately produce a turn-key capability to conduct benthic mapping surveys and to our knowledge, this is the only emerging product of this type.

Although certain aspects of the algorithms are designed for the SHOALS and CASI systems, the software should be extensible to work with any combination of sensors.

## TRANSITIONS

It is our intent to commercialize the REA processor and to promulgate its use for a wide range of benthic mapping applications. For the past year, the Joint Airborne Lidar Bathymetric Technical Center of Expertise (JALBTCX) has served as a beta test site for this software.

The basic functionality of the algorithms will be adopted into the next generation of bathymetric systems to be built by Optech at its offices in Kiln, Mississippi.

## RELATED PROJECTS

(1) *Coastal Zone Mapping and Imaging Lidar (CZMIL)*. CZMIL is a strategic partnership between Optech International and the Department of Marine Science at the University of Southern Mississippi leading to the design and construction of a next generation bathymetric lidar to improve performance in shallow water, and achieve water column and seafloor characterizations. The CZMIL project will also establish an industry/government/academic center of expertise for bathymetric lidar.

(2) *High-level Data Fusion Software for SHOALS-1000<sup>TH</sup>*. A National Ocean Partnership Program (NOPP) partnership between Optech International and the Department of Marine Science at the University of Southern Mississippi which addresses theoretical aspects associated with how to best combine data from multiple sensors, extend data fusion onto the beach environment, and collected in situ measurements to support characterization of the water column.

## REFERENCES

- [1] Tuell G.H. and Park J.Y. “Use of SHOALS Bottom Reflectance Images to Constrain the Inversion of a Hyperspectral Radiative Transfer Model”, Proc. SPIE Vol. 5412, Laser Radar and Technology Applications IX, G. Kammerman Ed., p. 185-193., 2004.